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Enhanced Track Faults Image Detection of track Linear Discrimination Analysis for Machine Learning Method

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Abstract

Railway transportation is one of the most important modes of passenger and freight movement worldwide. However, accidents caused by track flaws, impediments, and human or animal intervention continue to raise major safety issues. Traditional inspection and monitoring systems are primarily manual, resulting in slower defect detection and lower accuracy. This study offers an automated and intelligent railway monitoring system that uses real-time data collecting, processing, and alarm mechanisms to improve operational safety. This research presents an integrated method to improving railway track safety and reliability through auditory analysis, computer vision, and real-time monitoring. The system accurately detects track problems by evaluating data from a rolling camera installed on a self-driving vehicle. It also has fire detection and engine detachment methods for real-time monitoring. Also, itFurthermore, it enhances platform availability updates by optimizing train operations and passenger management with sophisticated scheduling algorithms. It offers a complete system for track maintenance and safety management and has demonstrated notable increases in safety standards through experimentation. In order to identify the crucial gap between an algorithm's performance and its possibility for deployment on hardware architectures to create dependable, real-time systems, this study focuses on the TLDA algorithm. This analysis assesses these methods' potential for real-time onboard deployment, points out their shortcomings, and suggests a new embedded multisensory system that will strike a compromise between scalability, energy economy, and performance.

Keywords: Deep learning (DL), defect detection, embedded systems, MobileNetv6, Feature Extraction, Track Linear Discriminant Analysis, Polyline Annotation.

Introduction

The railway sector is facing tremendous technical hurdles, which are exacerbated by the desire for digitalization, rising operational costs, more reliance on outsourcing, and rising logistical complexity, all within the larger context of environmental sustainability. The technology advancements in this sector (unmanned planes and autonomous vehicles in exclusive right-of-way or multiuser contexts), the diversity of professions served, and environmental and societal constraints all contribute to its complexity. With the goal of giving the final

consumer better service, railway firms are increasingly using high-performance systems that can be implemented with short lead times while optimizing costs.
Artificial intelligence (AI) is a key component of the systems that have been developed in recent years in an attempt to address this complexity. The growing complexity of railway systems and the requirement to maintain high performance to satisfy consumer expectations for regularity, comfort, and safety present the railway industry with two major and frequently competing issues.

The integration of contemporary technologies, a variety of operational requirements, and strict social and environmental restrictions all contribute to this complexity. The electricity system, rolling stock, and infrastructure (signaling, tracks, and engineering structures) are the three primary parts of the railway system. The two most important of them are rolling stock maintenance and infrastructure maintenance, which have a big impact on the level of customer service.

In Europe and around the world, railway safety continues to be a social and infrastructure priority. EU railway systems are among the safest in the world, according to the most recent analyses by the European Union Agency for Railways (ERA). However, following a period of stability in 2018–2021, a number of significant incidents were reported in 2022–2023, reminding us of ongoing vulnerabilities in protection against human factors, infrastructure failures, and level-crossing incidents [11]. Although the overall number of victims has decreased, accidents at road-rail crossings and track invasions continue to account for a significant portion, according to UIC (International Union of Railways) figures for 2023 [15].

The continual need to lower grade-crossing crashes, derailments, and pedestrian-related occurrences in the US is documented in the FRA (Federal Railroad Administration) database, which highlights the need for inspection automation, risk prediction, and quicker operational reaction [3]. A vital component of contemporary transportation, the railway industry necessitates ongoing innovation to handle its intrinsic operational and technical challenges. Aging infrastructure, increasing traffic needs, and high passenger and freight operator expectations all contribute to these issues. In order to address these issues, maintenance procedures must change from conventional remedial methods to predictive systems, utilizing cutting-edge technology to guarantee dependability, security, and affordability.

In the USA and Europe, railway maintenance is a major problem. The 2023 Annual Safety Report in France reveals serious flaws, with track faults accounting for 30% of infrastructure incidents, mostly as a result of inadequate or postponed maintenance [15]. The operating lifespan of more than 40% of rural railway lines is exceeded, posing operational and safety risks.

Related Works

[Kumar and others, 25] [1] describes the image processing has several practical uses in the railway industry that enhance efficiency, safety, and maintenance. In order to identify flaws or anomalies in the tracks, switches, and signals, image processing techniques are used in automatic rail infrastructure inspection, a crucial application. This helps with preventative maintenance and reduces the likelihood of accidents. Surveillance systems that keep an eye on railroad lines and stations for trespassers or suspicious activity also use image processing. It also aids in autonomous train tracking and identification, which makes efficient train scheduling and operation optimization possible. Image processing is essential to the safe and efficient operation of trains.

Holoborodko et al.'s [2025] [14] simulation to track signalling energy characteristics and identify anomalous activity at the same time. MATLAB (24.2.0.2863752 (R2024b) Update 5) simulations of a real double-track railway line under typical operating conditions and under a ransom warecyber attack scenario were used to validate the authors' model. The AI simulation model effectively detected an impending cyber attack 20 minutes prior to the event and accurately forecasted the signalling system's resilience, with an average absolute error of 0.0331 in predicting the fundamental performance indicator. This study highlights the AI-based signaling system's potential architecture, which significantly boosts resilience to power supply and cyber attack emergencies [3].

A viable strategy for enhancing the resilience and safety of railroads is the use of AI to optimize the signalling system, ensuring safe and uninterrupted train movement even in emergency situations. Walter et al. The proposer must oversee the demonstration of compliance with the safety requirements arising from the risk assessment phase prior to the change's safety acceptance. Any dangers found during the demonstration of compliance with the safety requirements, or any insufficiency of safety measures expected to fulfil the safety criteria, will cause the proposer to revaluate and analyse the related risks.

A robot called the Underfloor Inspection Vehicle can visually inspect maintenance and siding tracks.
According to Wang et al. (2025), edge detection encompasses a wide variety of hardware platforms [8]. The growth of the Internet of Things (IoT) and the requirement for real-time data processing have fuelled the rapid development of artificial intelligence (AI) technologies, which has resulted in an increased deployment of AI models on edge and terminal devices. The present status, technological difficulties, and potential developments of on-device AI models are all thoroughly examined in this survey. We characterize on-device AI models as those intended to carry out local data processing and inference, highlighting features such improved data privacy, resource limits, and real-time performance.

The survey is organized around major issues, such as the technical difficulties encountered in edge environments, application scenarios in a variety of sectors, and the basic ideas of AI models. We also go over implementation and optimization techniques that are critical to successful deployment, like hardware acceleration, model compression, and data pre-treatment. We also look at how new technologies, such as foundation models and edge computing, affect the development of on-device AI models. This survey intends to support additional study and use of on-device AI by offering a comprehensive overview of the problems, solutions, and future directions, ultimately advancing intelligent systems in daily life.

Perez-Cerrolaza et,al [14] associates a structural framework that guarantees the safe and coordinated operation of all railway infrastructure components is known as the railway signaling system. This component's non-operation results in violations of the railways' technical and transportation algorithms. It is crucial to maintain a continuous functioning mode in the face of cyberattacks and variations in energy savings. The importance of this area is shown by recent occurrences.

Proposed Work

Problem Identification

In order to ensure rail safety, track image detection utilizing machine learning locates and detects rail surface faults (fractures, corrosion, missing fasteners) from camera-captured video. It often addresses issues like small defect sizes and complex environmental backgrounds by classifying track conditions (normal/faulty) and creating bounding boxes around defects in real time. In object tracking, monocular cameras are frequently utilized. A computer vision system that uses a single camera to gather information from a single image from the camera is referred to as a monocular camera. Although it is challenging to determine the depth from a single image, some researchers use many monocular cameras and the principles of stereoscopy to determine the target object's three-dimensional position.

Given the benefits and drawbacks of monocular vision, many techniques are created using the data from a single image or a modified system that combines several monocular cameras, ultimately leading to uncalibrated stereo vision. Monocular cameras become an appropriate choice in certain applications where camera availability and cost are significant factors.

Object Tracking Benchmark (OTB) Dataset

A standardized collection of annotated video sequences used to assess, contrast, and train computer vision tracking systems is called an Object Tracking Benchmark (OTB) dataset. It makes it possible to test tracker accuracy, robustness, and speed objectively against typical difficulties by providing labeled "ground-truth" positions for objects (such as bounding boxes) between frames. One of the most significant and active fields of computer vision research has been object tracking. Recent years have seen the proposal of numerous tracking algorithms with proven effectiveness. However, for particular kinds of algorithms, the set of sequences utilized for evaluation is frequently insufficient or biased.

Comparing the stated quantitative results is challenging since many datasets lack similar ground-truth object locations or extents. Additionally, the analyzed tracking algorithms' initial conditions or parameters differ, making the quantitative results published in the literature different or occasionally conflicting. In order to overcome these problems, we conduct a thorough assessment of the most advanced online object-tracking algorithms using a variety of evaluation criteria in order to comprehend how different techniques function within the same framework.

Image Data Loading

Because of their straightforward structure, object detection-centric techniques frequently achieve fairly fast inference speed and generally decent inference accuracy, which makes them appropriate for scenarios with high

real-time needs and devices with limited processing resources. In this study, the SegNet mode was trained and assessed using a dataset of 2,000 railway track photos, divided into training and testing sets of 70% and 30%, respectively. Every image uses 640x480 pixels.

Sparse Data Acquisition

Maintaining railways and developing strategies to reduce noise and vibration depend heavily on ongoing rail condition monitoring. Vibro-acoustic measurements employing onboard sensors are an effective way to monitor rail. Large volumes of acoustic and vibration data are produced by this method, which presents difficulties for real-time transmission, processing, and storage. In order to address these issues, a sparse coding framework that is applied in the time-frequency domain is presented in this research. This framework drastically reduces the amount of data while maintaining crucial information for the diagnosis and detection of rail defects.

As a preprocessing step, the Short-Time Fourier Transform converts unprocessed data into a time-frequency representation that captures its non-stationary properties. A sparse linear combination of base spectra, which create a dictionary, is then used to represent the spectrum at each time window. A data-driven, adaptive representation that is specific to the frequency characteristics of vibro-acoustic sounds associated with rail problems is created using online sparse dictionary learning. The framework is evaluated using experimental data collected using an accelerometer and microphone installed on a tram's wheelset. The framework can achieve high compression rates and decrease noise, according to the testing results. Without sacrificing relevant information, a 98% reduction in data size was achieved.

The suggested method has many benefits for contemporary railway condition monitoring systems. It is energy-efficient, scalable for massive data sets, and appropriate for real-time deployment. It makes effective track tracking with on-board sensors possible by lowering data bottlenecks. Thus, this effort aids in the creation of clever and economical infrastructure management systems.

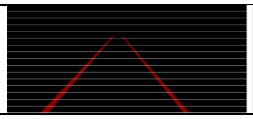
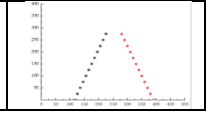
Polyline Image Annotation

Rail lines and other linear structures in photos and movies can be defined using a technique called polyline image annotation. In order to sketch the shape of these structures, this method entails drawing tiny lines connected at their vertices. It is especially helpful in applications where precise lane recognition is essential for safe and trouble-free driving, such as autonomous vehicle perception models. AI algorithms can learn to identify and navigate the Polyline image by labeling road lanes and other linear features. Annotation is a technique used by automated trains and free-driving track vehicles.

Image annotation establishes all label flaws as well as the standards that the model attempts to replicate. Consequently, more precise image annotation is even regarded as one of the most important tasks in computer vision. Annotation of images must be done by hand, although it can also be done automatically using the annotations application's tool. While simple tasks like classification just require tag-level annotations, jobs like segmentation and object recognition require pixel map annotations or bounding box annotations in the data.

Multi Object Rail Tracking –Feature Extraction-MobileNetV2

On the Y-axis, the image is split equally at 25-pixel intervals. The background and rail pixels show a distribution of "background + left rail + background + right rail" along a dividing line, which corresponds to a "0-1-0-1" arrangement in the output matrix. The coordinate information of the pixel locations on the left and right rails is computed by iterating through each dividing line. The average values of these coordinates are then retrieved to produce the characteristic coordinates of the left and right rails, as shown.

Real Image	Feature Extraction	MobileNetV2
		

An improved version of MobileNetV1, MobileNetV2 preserves simplicity, does away with special operators, and increases accuracy. Instead of using normal convolution, the MobileNetV2 network uses Depthwise Separable Convolution, which lowers the number of parameters and computational overhead. Using an inverted

residual structure, MobileNetV2 first increases the dimensionality, then performs a 3 × 3 Depthwise Separable Convolution, and then reduces the dimensionality.

Even at low precision, good numerical resolution is ensured by selecting ReLU6 as the activation function in the inverted residual structure. In order to preserve the richness of feature information and avoid excessive input compression, as might happen with Depthwise Separable Convolution, the inverted residual structure is used. This design strategy preserves a richer collection of features by keeping larger feature maps, which further improves feature extraction capabilities as compared to the residual architecture used in ResNet. Depthwise Separable Convolution is also used by the Xception network, although its structure is more intricate because it uses several of these routes, each with a unique set of parameters. Because of this, Xception usually has more parameters than MobileNetV2. The MobileNetV2 network's block structure.

Semantic Segmentation

Semantic segmentation is a computer vision technique that classifies every pixel in an image into a specific category, such as road, person, or sky, enabling precise pixel-level understanding of visual scenes. It differs from instance segmentation by labeling all pixels of a class (e.g., all cars) with the same label rather than separating individual objects.

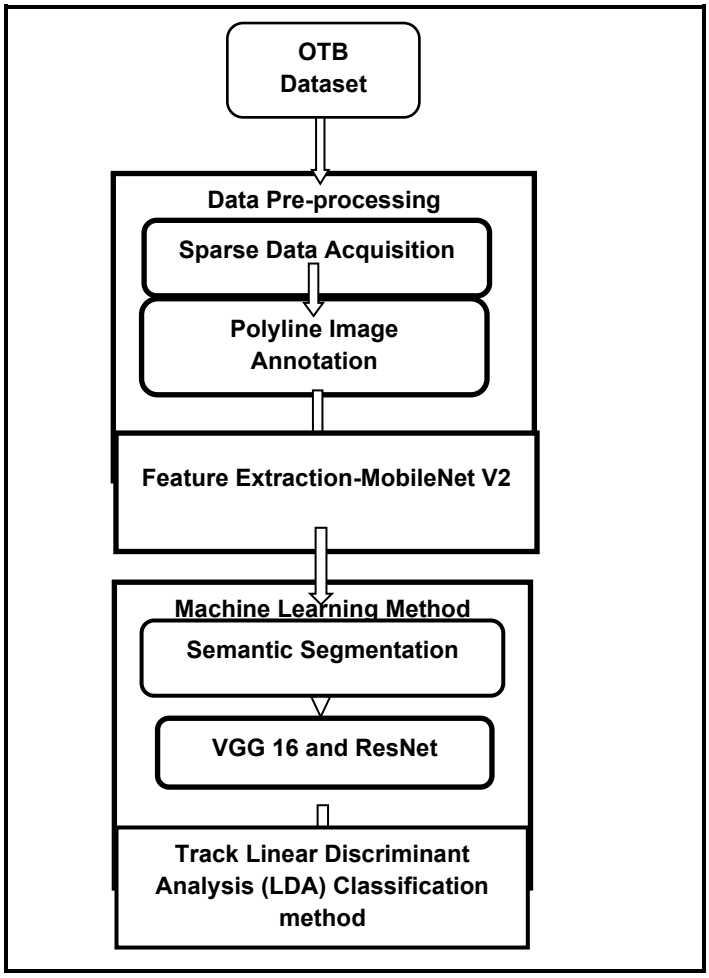


Fig. 3.1 Flow Diagram of Track Linear Discriminant Analysis (TLDA) classification Method

VGG-16 and ResNet

VGGNet consists of 16 convolutional layers. With such a few uniform layers and its impressive capability makes this an appealing network. Trained on 4 GPUs for 2–3 weeks. It is currently the most preferred choice in the community for extracting features from images. The configuration of the VGGNet is publicly available and has been used in many other applications and challenges as a baseline feature extractor.VGG-16 architecture include 3 × 3 filters organized in a sequential configuration of 64, 128, 256, and 512 filters. Additionally, a 2 × 2 Max

pooling layer is used to diminish the data volume, whilea2×2Upmaxpoolinglayerisutilized to augment the data size. The indices acquired during the downsampling step are used throughout the decoding process to improve the accuracy of picture resolution recovery.

Proposed TLDA Algorithm

Step 1:	Input OTB dataset
Step 2:	Sparse Data Acquistion: Time-series vibration data and Acoustic Wareform
Step 3:	Polyline Image Annotation- Noise Filtering and segmentation in time window
Step 4:	Frequency – Spectral Energy
Step 5:	LDA finds a projection that maximizes class separation: $w=Sw-1(\mu1-\mu2)$
Step 6:	For multiple classes, LDA generalizes to multiple discriminant axes.
Step 7:	Classify fused using NN classifier
Step 8:	Logistic Regression
Step 9:	Crack Initiation-Severe Fault
Step 10:	Frequency Spectrum, Texture features, alert
Step 11:	Surface Crack – UltraSonic Testing for Internal Crack
Step 12:	End

TLDA Algorithm

A supervised machine learning approach called Linear Discriminant Analysis (LDA) is used in railway track crack detection to divide sensor data or photographs into two groups: normal (crack-free) and cracked. It is highly regarded for its capacity to minimize dimensionality while optimizing the separability between these two classes, frequently attaining excellent accuracy at a lower computational cost than sophisticated deep learning techniques like CNNs.

Results And Discussion

The TLDA approach can effectively collect and integrate hierarchical data, it is particularly robust when dealing with anatomical structures with irregular forms or tiny lesions. Additionally, the skip connections reduce the possibility of data loss during feature down sampling, and the symmetrical construction of the encoder and decoder circuits permits efficient learning and optimization.

IoU

One important performance metric for railway track detecting systems is the intersection over union (IoU) metric. It calculates the overlap between the detected objects and the expected bounding boxes. An improved

detection accuracy is indicated by a higher IoU value. IoU metrics are essential for assessing the efficiency of detection algorithms and guaranteeing the security and other dependability of railway operations.

$$IoU = \frac{AreaofIntersection}{AreaofUnion} \text{-----(4.1)}$$

By overlapping the predicted bounding box and the ground truth bounding box, this formula ensures consistent assessment criteria, a shared bounding box, and a common ground for comparison. Based on a predetermined IoU threshold, it is critical for identifying true positives, false positives, and false negatives—all of which are necessary for precise railway track recognition.

Recall

Recall in train track image detection measures how well a system can identify all actual train track fault detection. It indicates the ability of the system to detect track without missing them**.**

$$Recall = \frac{TP}{TP+FN} \text{---------(4.2)}$$

MAE

The average of the absolute discrepancies between the expected and actual values is determined by mean absolute error. Although it provides a clear picture of the model's prediction accuracy, it does not indicate whether the errors are caused by over or underprediction. It is an excellent place to start when evaluating the model because it is easy to compute and understand.

$$MAE = \frac{1}{N}\sum_{j=1}^{n} |y_j - y_i| \text{----(4.3)}$$

Where:

- yjyj = Actual value
- y^jy^j = Predicted value

Accuracy

Overall classification accuracy is measured by accuracy. the proportion of actual positive expectations to the total number of positive projections produced by the model. It demonstrates how the model can correctly detect positive occurrences while limiting the incorrect classification of negative situations as certain.

$$Accuracy = \frac{TP+TN}{FP+FN} \text{ ----- (4.3)}$$

From fig 4.1 displays the proposed procedure produces superior TLDA outcomes relative to existing methods as shown in figure. The loss and accuracy for both the quantum and classical models are computed across the training and validation datasets.While comparing the existing methods such as Segnet, D-LinkNet, Random Forest. The proposed methods brings the better results of accuracy and IoU level.

Methods	**Original**	**Image Feature**	**Noise Reduction**	**Track-**

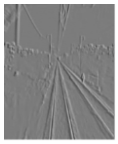
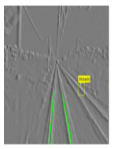
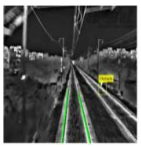
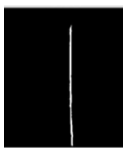
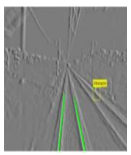
	Image			Fault Identify
SegNet				
D-Link Net				
Radom Forest				
TLDA				

Fig.4.1 Comparative Analysis of Enhanced table analysis TLDA classification algorithm in Railway Track Fault Detection

From Fig.4.1 describes the comparative analysis of enhanced track image analysis and compare the TLDA proposed method with existing methods in Railway Track Fault Detection. The proposed TLDA method not only display the Track fault identification also find the location of the fault and the centimetres of crack.

Table 4.1 Enhanced table analysis TLDA classification algorithm in Railway track fault detection

Methods	IoU	Recall	MAE	Accuracy
SegNet	**84.13**	**85.53**	**91.07**	**92.34**
D-Link Net	**85.47**	**92.31**	**92.64**	**92.22**
Radom Forest	**94.81**	**93.17**	**94.26**	**95.13**
TLDA	**95.11**	**95.21**	**95.24**	**96.81**

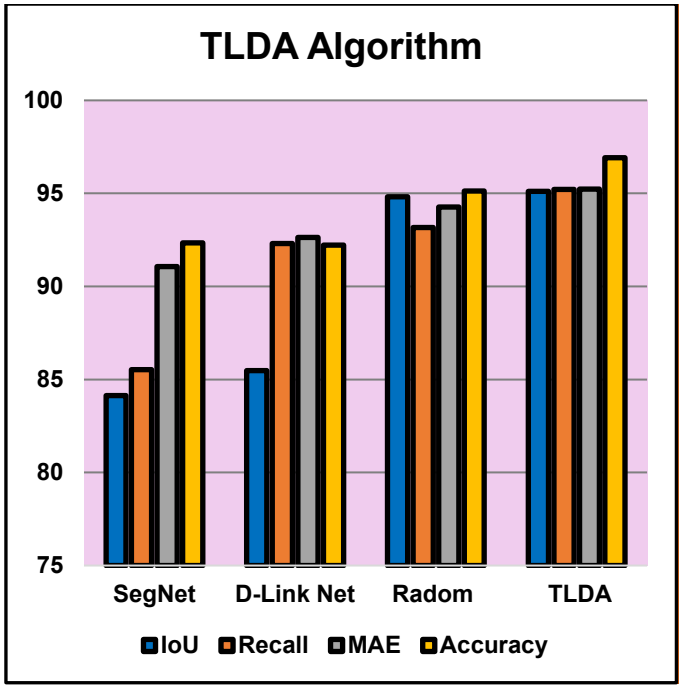


Fig.4.2 Enhanced table analysis TLDA classification algorithm in Railway track fault detection

From fig.4.2 this work enhances train track fault image detection by employing hybrid feature selection algorithms that integrate firefly and glowworm optimization techniques, utilizing the TLDA algorithm.

Conclusion

The main contribution of the proposed study Track Linear Discriminant Analysis classification technique is that image processing-based systems provide faster detection, better reliability, and the capacity to constantly monitor huge railway networks when compared to traditional manual inspection methods. By understanding intricate crack patterns under various environmental situations, such as illumination, shadows, and surface wear, advanced techniques, such as machine learning and deep learning models, significantly improve detection accuracy. Sensitivity to environmental noise, differences in track appearance, and the requirement for large, well-annotated datasets for training robust models are also obstacles. Notwithstanding these drawbacks, performance and scalability are being greatly enhanced by continuous developments in computer vision and artificial intelligence.

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